A Thesis for the Degree of Master of Science

Algorithms Predicting Attention and Memory Ability based on the Combination of Children′s Physiological Data

생리학적 데이터의 조합을 바탕으로 한 아동의 집중력, 기억력 예측 알고리즘

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Abstract

Good performance is regarded as important element not only in workplace but also in daily activities. Performance of the human depends on the mental capacity and mental workload. Performance declines when the mental workload exceeds mental capacity. The point the mental capacity is exceeded by mental workload is regarded to as the cognitive “redline” of workload. Performance declines faster at this point, as task demand is greater than the mental capacity. Few studies of the cognitive redline of workload have been done. In addition, for good performance, mental workload is regarded as more important than physical workload. Especially, according to piaget’s cognitive development theory, children in concrete operational stage is critical for further learning ability that they develop their ability to distinguish between quality and quantity. However, the reason that mental workload is difficult to quantify through physiological measures, makes it more complicated to demonstrate the cognitive redline. When it comes to children’s development, physical change is visible and easy to identify but mental change is not. Moreover, EEG which is one of the representative measuring tool of physiological data requires

accurate process of measuring and analyzing with the expert. HRV is relatively easy to measure but has limitation because it is indirect way of measuring brain signal. Above all things, many researches of real-time indicator measuring physiological data such as heart rate variability (HRV), skin conductance response (SCR) have been done sporadically but not integrated. Therefore, In this study I tried to demonstrate if i can predict the mental capacity (attention and memory ability) not mental workload with the EEG. In addition, with the combination of EEG and HRV, I tried to overcome disadvantages of physiological tool and tried to develop advanced algorithm which predicts mental capacity. Attention ability was measured with Stroop task, and memory ability was measured with digit span task. Elementary school students aged 6-13 were participated, whose brain development is in important phase according to Piaget theory. In conclusion, right-temporal EEG data significantly predicts attention score, and occipital EEG data significantly predicts memory score. I also analyzed brain wave EEG model, and found out beta EEG power significantly predicted attention score but not memory score. I also analyzed HRV data with all other physiological data to earn more predictable algorithms

model. These data can be used as daily performance parameter of attention and memory ability. However, in the further study more number of population are needed to increase the accuracy of the model. Moreover, Application which can collect and analyze physiological data needs to be more sophisticated and needs to be properly connected to wearable devices.

Keywords: Physiological data, EEG, HRV, combination, predicts, attention ability, memory ability, Algorithms model

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Contents

Ⅰ. Introduction

1.1 Mental capacity and mental Workload

Good performance is regarded as important element not only in workplace but also in daily activities [1]. Performance of the human depends on the mental capacity and mental workload. Therefore, performance of human decreases under the higher mental workload compared to their mental capacity [2], and Stress and fatigue negatively affect mental health which in the end affect sympathetic nervous system [3]. Most researchers call this decreasing point “redline” of cognitive workload [4]. The point the mental capacity is exceeded by mental workload is regarded to as the cognitive “redline” of workload. Also, redline can be expressed as threshold of point which performance starts to decrease [5]. Mental workload which overload the brain’s limitation causing one’s sharp decrease in performance [2]. Cognitive redline of workload can be explained with two areas depending on demanding tasks [6]. First, when there is less task compared to the one’s mental capacity, residual capacity

remains. Second, when there is more task than the limitation of brain information processing, performance constantly decreases. In other word, cognitive redline of workload can be defined with differences of two areas depending on task demand. Mental workload means a mental resource which is required to complete a single or multiple tasks in this context [4], and it means more task is existing than brain can actually can process [6]. Mental capacity is based on the theories regarding how much information can be processed and stored. Mental capacity can be limited with any other reasons and it can be over its capacity [7]. So, It is important to confirm acceptable levels of mental capacity and mental workload for the human [8]

1.2 Physiological measurements as a real time indicator

Breath rate (BR), heart rate (HR), heart rate variability (HRV), skin conductance response (SCR), and electroencephalography (EEG) are related to activation in sympathetic nervous system. If human operator is affected by mental health such as

stress, it activates sympathetic nervous system. It affects regulating functions such as Breath rate (BR), heart rate (HR), heart rate variability (HRV), skin conductance response (SCR), and electroencephalography (EEG) [9]. Many researchers use physiological data as real-time indicator to measure the mental workload compared to currently given task and mental capacity [1]. Another research using physiological data shows that increase in cognitive workload activates sympathetic nerve system and inactivates parasympathetic nervous system [10]. This means that increase in cognitive workload physiological measures changes until it reaches plateau [1]. Using Physiological measures as mental workload indicator has advantages that it can steadily measures user's real-time mental workload without disruption [11]. Physiological measures makes it possible to evaluate user's workload until it reaches mental capacity limitation. It is reliable measures and it can protect user's performance from decreasing [1].

1.2.1 Physiological measurement: Electroencephalography (EEG)

For integrated understanding of brain based cognition and behavior, multi-disciplinary researches using electroencephalography (EEG) is being developed [12, 13]. EEG shows accurate changes in signals regarding alertness, attention and workload. Changes can be identified and quantified with this tool depending on time. There are many researches demonstrating high correlation between changes in cognitive status and EEG indices under many circumstances such as workplace, stimulation [14-20]. The most basic method of analyzing cognitive status using EEG is to analyze the frequency band or to analyze the ratio between these bands [19-22]. Another analysis method is the N100 and P300 amplitudes which are components of the event-related potential (ERP) have been used in some cognitive assessment models [12, 23, 24]. There are many researches modeling correlations between EEG brain regions and spectral frequencies related to mental workload and spatial and

verbal processing [14, 25]. The EEG PSD bands or ERP component measurements were used as inputs to classifier models for allowance of identification and classification of cognitive signals such as mental workload, engagement, executive function, attention and memory ability. In addition, multivariate approach to researches have been suggested related to cortex activation which is recommended for task improvement [21, 26, 27].

1.2.2 Physiological measurements: Heart rate variability (HRV)

When it comes to Heart rate variability (HRV), it has been researched as important marker of autonomic nervous system (ANS) [28-30]. ANS is composed of sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) [31, 32]. SNS attenuation and PNS activation is related to high HRV, especially it is associated with high frequency component (HF) and higher prefrontal cortex (PFC)

[33]. Based on this, researches regarding HRV and cognitive performance were conducted [34, 35]. Participants with high HRV showed higher performance on executive tasks compared to participants with low HRV [31, 36].

1.3 Limitation of current physiological researches

Nowadays, more and more people try to maintain their health and prevent illness, and also they try to promote their quality of life with various options. Especially, we can keep track of individual's level of fatigue, attention, task engagement, and mental workload with physiological parameters under certain circumstances [14, 22, 23, 37, 38]. Likewise, in the healthcare area, physiological data have many benefits. However, it has many limitation to be used in daily life. EEG is rarely used outside of hospitals, and it has problem of high noise when collecting brain signals if used in daily life which means inaccurate and less effective [39]. EEG can be separately measured to analyze one's accurate cognitive status, but it needs accurate

measurement and analyzing time which makes it hard to be used in daily life. Also, ordinary people lack professional information to use EEG [40]. Heart rate variability has advantages of simple measuring process. However, HRV variable to measure is unclear conventional time domain, BRS, heart rate turbulence, spectral measures, geometric measures, and a variety of nonlinear variables shows different aspects of HRV and have been significantly related to outcome without clear, consistent superiority for any. In addition, isolated HRV measurements have limitation of predictive accuracy. As a univariate predictor, HRV has low sensitivity and low positive predictive accuracy. Moreover, there is limitation quantifying mental capacity and workload by physiological measures. To overcome this limitation, technical progression of physiological measurements are being made, however there are still lack of researches which integrates the various studies which is using physiological data as real-time indicator [8].

1.4 Cognitive development in children

One of the Piaget's theory, theory of cognitive development is a theory about the nature and development of human intelligence. The theory explains the nature of knowledge itself and how humans come to acquire, construct, and use knowledge. Piaget's theory is mostly known as a developmental stage theory [41]. Piaget's theory of cognitive development is composed of 4 stages which is sensorimotor, preoperational, concrete operational and formal operational period. Piaget demonstrated that childhood is crucial and important period regarding lifelong development of human.

1.5 My hypothesis

This study aims attention and memory ability of children who are in Concrete operational stage. In concrete operational stage, Children can discriminate changes in number and quantity. They have to develop attention and memory skills which is

important for learning task. The hypothesis of this study is to develop a prediction model which can predicts the children's attention and memory ability based on EEG brain region and brainwave. In addition, another physiological tool, HRV was added to the model to develop more accurate prediction model of attention and memory ability. The purpose of this study is to combine physiological tools to makeup the limitations of its own if used separately, and based on this, I suggests framework to simply predict children's attention and memory ability. Combined physiological data framework can provide real-time prediction of current attention and memory ability and its maximum capacity to simply check these. EEG and HRV were used to measure the physiological data and tasks of attention and memory ability were used to measure the mental capacity performance. Attention was measured with Stroop task, and memory was measured with digit span task. Elementary school students aged 6-13 were participated, whose brain development is in important phase according to Piaget theory.

Ⅱ. Materials and methods

2.1. Participants

Forty, right-handed elementary school students (22 females, 28 males, ages: 6-12) were participated in the study for two month. All subjects and their parents provided informed consent before participating, and the study was approved by the Institutional Review Board (IRB # 1703-001-002) at Seoul National University, Korea. Before measurement of physiological data, to check the symptoms of illness which can be crucially affect the attention and memory performance score, Mini international neuropsychiatric interview (M.I.N.I) were conducted to the participants and their accompanied parents for 5 minutes (fig. 1). Participants visited the laboratory on one occasion only. The Participants with BMI over 23 was excluded from the study and participants with the symptoms of ADHD were also excluded. Any food intake was prohibited from 2 hours before the experiment.

2.2. Procedures

In a quiet laboratory room, each participant was instructed to sit on a comfortable armchair. Participants were instructed about the procedure of the experiment (fig. 2A). Simultaneously, Mini international neuropsychiatric interview (M.I.N.I) were conducted to the participants and their accompanied parents for 5 minutes. And then, total 10 electrodes were placed on participant's brain according to 10-20% international standard system (2 electrodes each on prefrontal, right temporal, left temporal, occipital, parietal) (fig. 3). Resting EEG were measured for 11 minutes. As the experiment starts, participants closed their eyes and remained resting state for 5 minutes. And they open their eyes and rests for 1 minutes and then, closed their eyes again and remained resting state for 5 minutes again. Electrodes measuring heart rate variability were placed on back of both hands and right ankle (3 electrodes total). Attention and memory ability measurement task were conducted when measuring HRV simultaneously for 10 minutes. 3 stages of Stroop task were

conducted to measure attention ability performance (fig. 2B). After Stroop task, 2 stages of digit span task were conducted (forward and backward) to measure memory ability performance (fig. 2C). When HRV measurement ends, all the electrodes were eliminated and experiment ended.

Figure 1

W1. In the past six months:

A	Have you often not paid enough attention to details or made careless mistakes at work, in your schoolwork or in other activities?	N	Y
B	Have you often had trouble keeping your attention focused on tasks?	N	Y
C	Have you often been told you do not listen when others talk directly to you?	N	Y
D	Have you often had trouble following through with what you were told to do (like not following through or finishing duties at work, in schoolwork or chores)?	N	Y
E	Have you often had a hard time organizing tasks and activities?	N	Y
F	Have you often tried to avoid things that make you concentrate or think hard (like schoolwork)?	N	Y
G	Have you often lost or forgotten things you needed?	N	Y
H	Do you often get distracted easily by little things (like sounds or things outside the room)?	N	Y
I	Do you often forget to do things you need to do every day?	N	Y

W1 SUMMARY : ARE 5 OR MORE W1 ANSWERS CODED YES?	N	Y

W2. In the past six months:

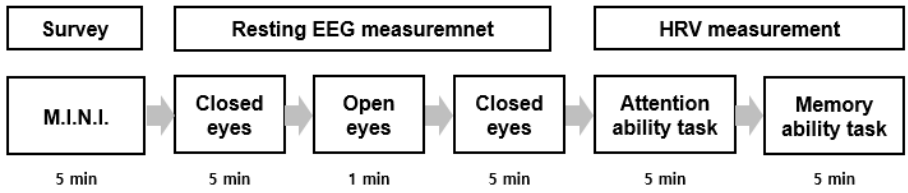
A	Did you often fidget with your hands or feet?	N	Y
B	Did you often get out of your seat when you were expected to remain seated?	N	Y
C	Did you often feelings of restlessness and want to move around a lot when you were not supposed to?	N	Y
D	Have you often had a hard time playing or doing leisure activities quietly?	N	Y
E	Were you always "on the go" or did you act as if you were driven by a motor?	N	Y
F	Have you often been told that you talked too much?	N	Y
G	Have you often blurted out answers or responses before the other person had finished the question?	N	Y
H	Have you often had trouble waiting your turn?	N	Y
I	Did you interrupt or interfere with someone else's activities?	N	Y

W2 SUMMARY : ARE 6 OR MORE W2 ANSWERS CODED YES?	N	Y
W3 Did you some of the symptoms of ADHD start before the age of 7?	N	Y
W4 Have you ever these symptoms caused serious problems in the following situations: school, work, home, family or friends	N	Y
W5 Is W4 YES?	N	Y

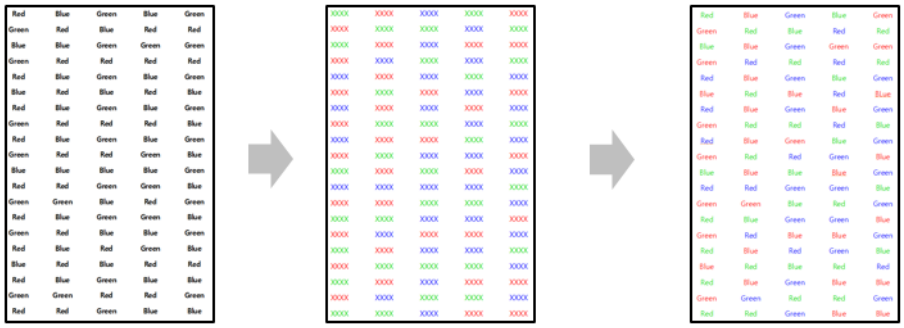
Figure 1. Mini international neuropsychiatric interview (M.I.N.I) were conducted to the participants and their accompanied parents for 5 minutes. ADHD subjects who were able to influence their concentration and memory scores through the questionnaire were excluded from the results analysis.

Figure 2

A



B



C

	Forward memory task		Backward memory task
(1)	3 · 8 · 6	(1)	2 · 5
	6 · 1 · 2		6 · 3
(2)	3 · 4 · 1 · 7	(2)	5 · 7 · 4
	6 · 1 · 5 · 8		2 · 5 · 9
(3)	8 · 4 · 2 · 3 · 9	(3)	7 · 2 · 9 · 6
	5 · 2 · 1 · 8 · 6		8 · 4 · 9 · 3
(4)	3 · 8 · 9 · 1 · 7 · 4	(4)	4 · 1 · 3 · 5 · 7
	7 · 9 · 6 · 4 · 8 · 3		9 · 7 · 8 · 5 · 2
(5)	5 · 1 · 7 · 4 · 2 · 3 · 8	(5)	1 · 6 · 5 · 2 · 9 · 8
	9 · 8 · 5 · 2 · 1 · 6 · 3		3 · 6 · 7 · 1 · 9 · 4
(6)	1 · 6 · 4 · 5 · 9 · 7 · 6 · 3	(6)	8 · 5 · 9 · 2 · 3 · 4 · 2
	2 · 9 · 7 · 6 · 3 · 1 · 5 · 4		4 · 5 · 7 · 9 · 2 · 8 · 1
(7)	5 · 3 · 8 · 7 · 1 · 2 · 4 · 6 · 9	(7)	6 · 9 · 1 · 6 · 3 · 2 · 5 · 8
	4 · 2 · 6 · 9 · 1 · 7 · 8 · 3 · 5		3 · 1 · 7 · 9 · 5 · 4 · 8 · 2

Figure 2. Experimental design. (A) Entire procedure of the experiment. (B) Procedure of the Stroop task. 3 stages of Stroop task were conducted to measure attention ability performance. (C) Numbers used for digit span tasks. Series of numbers were spoken to participants and then participants repeated this numbers in forward or backward order. 2 stages of digit span task were conducted (forward and backward) to measure memory ability performance

2.3. Physiological measurement

2.3.1 Resting state EEG recordings

A 32-channel EEG system (WEEG 32a) along with a customized EEG-based real-time brain mapping software (Telescan, LAXTHA Inc., Korea) was used to acquire data on the cortical activity in the experiment. Scalp electrodes (Ag-AgCl) on the specific locations were detected according to an extended 10/20 system. The procedure was conducted in an electrically shielded and sound attenuated experimental room. Electrodes were placed on prefrontal (Fp1, Fp2), left temporal (F7, T5), right temporal (F8, T6), parietal (Fz, Cz), occipital (O1, O2) areas of scalp (fig 3). All scalp electrodes were referred to linked electrodes placed on the left and right mastoid (right-reference, left-ground). Eye movements and blinks were eliminated by EOG filtering system using Telescan Software. Artifacts of electricity were filtered with FFT notch filter at 50Hz. FFT band filter at 0.2~45Hz (High-pass filter + low-pass filter) were used to eliminate moving noise. The EEG was recorded

continuously with 0.7–46 Hz analogue bandpass and a sampling rate of 512 Hz.

2.3.2 Heart rate variability measurement

Heart rate variability (HRV) were used with MP-100 equipment (BIOPAC systems, Inc). Analog input no.1 were used to check the equipment, analog input no.2 were connected to HRV measurement (fig. 4). Acquisition sample rate were 2000(samples/second) and it was being measured for 10 minutes. Electrodes measuring heart rate variability were placed on back of both hands and right ankle (total three electrodes). Data were analyzed with acknowledge 3.9.1 software. Very low frequency PSD, low frequency PSD, high frequency PSD, Very high frequency PSD, sympathetic, vagal, sympathetic-vagal balance were analyzed.

2.4. Stroop task

The Stroop effect has been used to investigate a person's psychological capacities. Its discovery during the twentieth century, it has become a popular neuropsychological test. This test is considered to measure selective attention, cognitive flexibility and processing speed, and it is used as a tool in the evaluation of executive functions. In this study, Stroop task were used to measure selective attention. The Selective Attention Theory that color recognition as opposed to reading a word, requires more attention, the brain needs to use more attention to recognize a color than to word encoding, so it takes a little longer. Total 3 stages were conducted (fig 2B). Each stages has limitation of time (40 seconds). After the task, total number of words which were read correctly were counted. In the first step, participants spoke out the black-printed word (ex> red). After the first step, participants asked to spoke out the color-printed word. In the last stage, they spoke out the color of the words, not the

meaning of the words (ex> blue). After all steps ended, the score of step2 and step3 were converted into T-score to eliminate the effects of age.

2.5. Digit Span task

Participants conducted the digit span memory task to measure working memory capacity [42]. Digit span task were composed of both forward and backward memory task. Digits read aloud. Participants were required to give immediate ordered recall. At a particular span length, if the participants recalled digits correctly, the span length was then increased by two digits. Span was taken as the maximum length if performed without error. However, if participants answered wrong 2 times consequently, the task ended and number of correct answers were calculated as score [43]. In the first trial they spoke out the digits in order (forward), but in the second trial they did it in reverse order (backward). After all steps ended, the score of step2 and step3 were converted into T-score to eliminate the effects of age.

2.6. Data analysis

EEG data, HRV data, and the scores of the tasks of 50 participants were analyzed. EEG data and HRV data were used as independent variable. Attention and memory task score were used as dependent variables. In the further analysis with EEG electrode T6 were eliminated because of technical problem. HRV data of 36 participants were analyzed. Rest of data were eliminated because of measuring error. 2 ways of analyzing tools were used to demonstrate the correlation of EEG, HRV and attention. First, multiple regression were conducted depending on brainwaves (alpha, beta, gamma, delta, theta). To reproving if the model is available F examination were conducted under 0.05 significance. In the model which is significantly meaningful, comparison of R^2 (adjusted R^2) were conducted. ANOVA examination were conducted to analyze the significance of variables. With the same analyzing tools, correlation of EEG, HRV, and memory tasks were analyzed with multi-regression test and significance of variables were also examined [44].

Figure 3

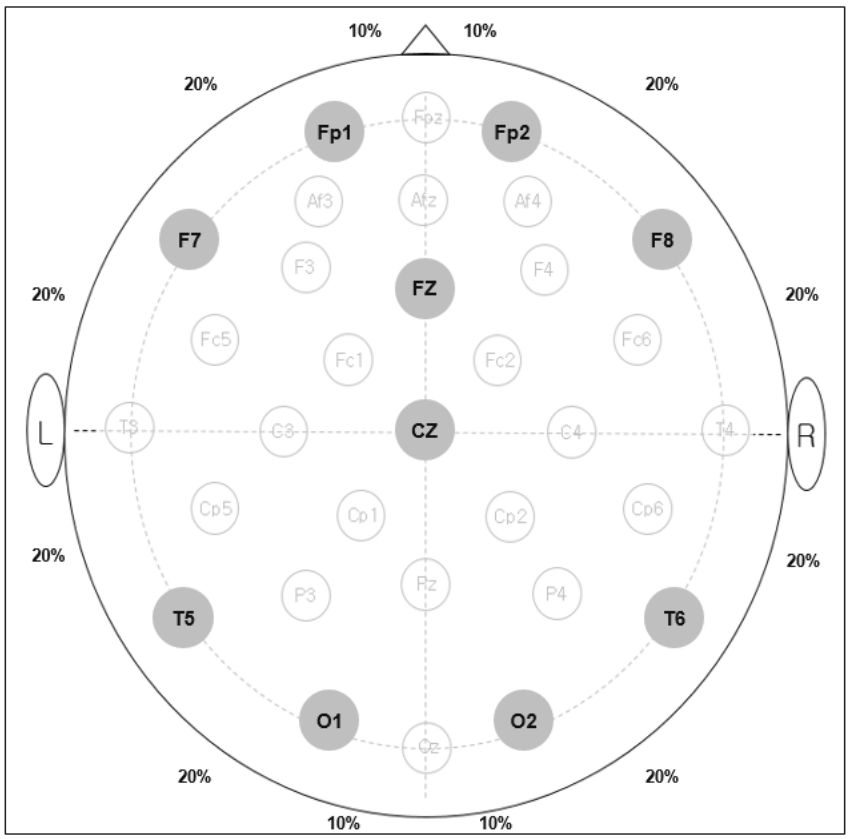


Figure 3. Location of 10 electrodes based on 10/20 system. Prefrontal regions (Fp1, Fp2), right temporal regions (F7, T5), left temporal regions (F8, T6), parietal regions (Fz, Cz) and occipital regions (O1, O2) were regions of interest.

Figure 4

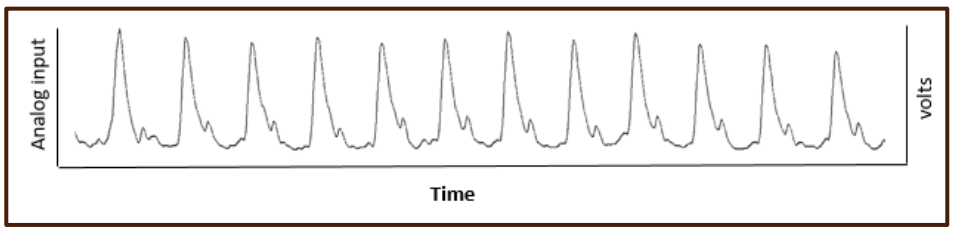


Figure 4. Analog input were connected to HRV measurement. Acquisition sample rate were 2000(samples/second) and it was being measured for 10 minutes.

Ⅲ. Results

3.1. Most predictable attention and memory ability algorithm model based on ROI (EEG) analysis

Among the electrodes which was placed two per each area, I tried to figure out which area most accurately predicts attention and memory ability. Stroop task was used to measure selective attention ability (fig. 2B: t-score of step2-step3). Digit span task were used to measure working memory capacity (fig. 2C. t-score of forward + backward).

3.1.1. Right temporal (F8) is the most predictable attention ability algorithm model and Addition of HRV data to attention ability algorithm model increases prediction accuracy.

F8 electrode in right temporal area was proved to be significant model ($p<0.05$)

($r=0.2814$, $p<0.0210$) (fig. 5A). Attention ability prediction algorithms formula is Attention ability score = 49.78965 - 0.02776*(F8, ß) + 0.07511*(F8, δ) - 0.08827*(F8, γ) + 0.81112*(F8, θ). With the previous model, HRV data (Sympathetic-vagal balance) were added and analyzed again to check the correlation with the attention ability. F8 electrode in right temporal area was proved to be significant model ($p<0.05$) and added data increased the accuracy of the model. ($r=0.2814 \rightarrow 0.3175$, $p<0.0210 \rightarrow 0.0403$) (fig. 5B). Attention ability prediction algorithms formula is Attention ability score = 24.1488 + 0.1901*(F8, ß) + 0.3024*(F8, δ) + 0.1465*(F8, γ) + 1.0506*(F8, θ) + 1.8506*(HRV).

Figure 5

A

Electrodes	P-value	R-squred
Fp1	0.2896	0.1327
Fp2	0.3168	0.1263
O1	0.3415	0.1209
O2	0.8919	0.03137
F7	0.4727	0.0961
F8	**0.0210**	**0.2814**
T5	0.3770	0.1137
FZ	0.1479	0.1763
CZ	0.4901	0.0931

B

Electrodes	P-value	R-squred
Fp1	0.0961	0.2644
Fp2	0.2226	0.2047
O1	0.494	0.1344
O2	0.7729	0.0795
F7	0.4606	0.1415
F8	**0.0403**	**0.3175**
T5	0.4374	0.1466
FZ	0.1481	0.2349
CZ	0.4987	0.1334

Figure 5. Multi-regression analysis based on brain regions were used between 10 electrodes and attention ability score. (A) When using only EEG data, F8 electrode in right temporal area was proved to be significant model ($p<0.05$) ($r=0.2814$, $p<0.0210$). (B) When the HRV data were added to the previous analysis, F8 electrode in right temporal area was proved to be significant model ($p<0.05$) and added data increased the accuracy of the model. ($r=0.2814 \rightarrow 0.3175$, $p<0.0210 \rightarrow 0.0403$).

3.1.2 Occipital (O2) is the most predictable memory ability algorithm model and Addition of HRV data to memory ability algorithm model increases prediction accuracy.

Forward digit span task is related to working memory ability especially phonological loop system and backward digit span task is also related to working memory especially central executive system [45]. O2 electrode in occipital area was proved to be significant model ($p<0.05$) ($r=0.3069$, $p<0.0122$) (fig. 6A). Memory ability prediction algorithms formula is memory ability score = -11.28313 + 0.18673*(O2, ß) + 0.77447*(O2, δ) + 0.24961*(O2, γ) + 1.88056*(O2, θ). With the previous model, HRV data (Sympathetic-vagal balance) were added and analyzed again to check the correlation with the memory ability. O2 electrode in occipital area was proved to be significant model ($p<0.05$) and added data increased the accuracy of the model. ($r=0.3069 \rightarrow 0.4481$, $p<0.0122 \rightarrow 0.0028$) (fig. 6B). Memory ability prediction algorithms formula is memory ability score = -9.59049 + 0.16593*(O2, ß) + 0.75304*(O2, δ) + 0.16499*(O2, γ) + 1.81548*(O2, θ) + 0.60024*(HRV).

Figure 6

A

Electrodes	P-value	R-squred
Fp1	0.2078	0.1549
Fp2	0.1429	0.1784
O1	0.1579	0.1723
O2	**0.0122**	**0.3069**
F7	0.7579	0.0523
F8	0.4431	0.1013
T5	0.1696	0.1678
FZ	0.7927	0.0471
CZ	0.6878	0.0626

B

Electrodes	P-value	R-squred
Fp1	0.2720	0.1887
Fp2	0.1659	0.2268
O1	0.1142	0.2529
O2	**0.0028**	**0.4481**
F7	0.9420	0.0395
F8	0.6352	0.1063
T5	0.3083	0.1783
FZ	0.7173	0.0904
CZ	0.6826	0.0971

Figure 6. Multi-regression analysis based on brain regions were used between 10 electrodes and memory ability score. (A) When using only EEG data, O2 electrode in occipital area was proved to be significant model ($p<0.05$) ($r=0.3069$, $p<0.0122$). (B) When the HRV data were added to the previous analysis, O2 electrode in occipital area was proved to be significant model ($p<0.05$) and added data increased the accuracy of the model. ($r=0.3069 \rightarrow 0.4481$, $p<0.0122 \rightarrow 0.0028$).

3.2 Most predictable attention and memory ability algorithm model based on Brain wave (EEG) analysis

Among the electrodes which was placed two per each area, I tried to figure out which brain wave most accurately predicts attention and memory ability. Stroop task was used to measure selective attention ability (fig. 2B: t-score of step2-step3). Digit span task were used to measure working memory capacity (fig. 2C: t-score of forward + backward).

3.2.1 Beta wave is the most predictable attention ability algorithm model and Addition of HRV data to attention ability algorithm increases prediction accuracy.

Beta wave was proved to be significant attention algorithm model ($p<0.05$) ($r=0.4610$, $p<0.0184$) (fig. 7A). Attention ability prediction algorithms formula is Attention ability score = 43.5799 + 0.3917*(Fp1, ß) - 0.4448*(Fp2, ß) + 0.1833*(O1,

ß) + 0.4074*(O2, ß) + 1.2066*(F7, ß) - 0.6268*(F8, ß) - 0.5555*(T5, ß) + 0.4602*(Fz, ß) - 0.9039*(Cz, ß). With the previous model, HRV data (Sympathetic-vagal balance) were added and analyzed again to check the correlation with the attention ability. Therefore, brainwave was proved to be significant model ($p<0.05$) and added data increased the accuracy of the model. ($r=0.4610 \rightarrow 0.5202$, $p<0.0184 \rightarrow 0.0267$) (fig. 7B). Attention ability prediction algorithms formula is Attention ability score = 22.9784 + 0.2330*(Fp1, ß) + 0.0411*(Fp2, ß) + 0.0312*(O1, ß) + 0.3433*(O2, ß) + 0.9397*(F7, ß) - 0.6113*(F8, ß) - 0.4559*(T5, ß) + 0.5807*(Fz, ß) - 0.8148*(Cz, ß).

3.2.2 There was no brain wave which can predict memory ability. However, with the addition of HRV data, there was increase in predictability in the model.

There was no brain wave which can predict memory ability score (fig. 7C). However, with the addition of HRV data, there was increase in predictability in the model (fig. 7D).

Figure 7

A

Brain wave	P-value	Multiple R-squred
Alpha	0.1630	0.3313
Beta	**0.0184**	**0.4610**
Gamma	0.4776	0.2330
Delta	0.0258	0.4440
Theta	0.0517	0.4062

B

Brain wave	P-value	Multiple R-squred
Alpha	0.2935	0.3485
Beta	**0.0267**	**0.5202**
Gamma	0.4399	0.3029
Delta	0.0603	0.4728
Theta	0.1288	0.4203

C

Brain wave	P-value	Multiple R-squred
Alpha	0.7914	0.1556
Beta	0.7282	0.1723
Gamma	0.9577	0.0929
Delta	0.6926	0.1812
Theta	0.5488	0.2157

D

Brain wave	P-value	Multiple R-squred
Alpha	0.8439	0.1839
Beta	0.9694	0.116
Gamma	0.6715	0.2384
Delta	0.3017	0.3457
Theta	0.6981	0.2308

Figure 7. Multi-regression analysis based on brain waves were used between 5 brain waves and attention and memory ability score. (A) When using only EEG data, Beta wave was proved to be significant attention ability model ($p<0.05$) ($r=0.4610$, $p<0.0184$). (B) When the HRV data were added to the previous analysis, beta wave was proved to be significant model ($p<0.05$) and added data increased the accuracy of the attention ability model. ($r=0.4610 \rightarrow 0.5202$,

$p<0.0184 \rightarrow 0.0267$). (C) There was no brain wave which can predict memory ability score. (D) With the addition of HRV data, there was increase in predictability in the model.

Ⅳ. Discussion

In this study, I tried to make a framework which can predict attention and memory with the most accuracy by selecting most predictable, area and brain wave which can be measured with EEG.

4.1. With the specific area (temporal,F8) and specific brainwave (beta wave), Attention can be predictable. Moreover, with the addition of HRV data, predictability increased. As a result, temporal (F8) and beta wave predicts attention mostly.

In this study, I aimed to develop simple framework which can predicts attention mostly with the brain area which was measured with EEG and brainwave. Analyzing several brain areas and brainwaves at the same time, I found out most predictable variables. I did not analyze each variable separately. So it is not yet to be concluded

to physiological phenomenon. However, in the previous study, damage on temporal area affects attention ability, especially, with the frontotemporal atrophy, one can be fragile to Pick's disease which is related to cognitive function [46]. Moreover, there is study regulating selective attentional modulation by placing short foreperiod on temporal area. Framework can be made with the brainwave, especially beta wave and delta wave, which can predict attention mostly. Originally delta wave is well known as sleep related brainwave and beta wave is well known for its arousal and attention. So I made attention formula with the beta wave which is reasonable. I used EEG as major tool because it directly measures EEG brain signal so it is more accurate tool to measure one's cognitive status compared to other devices (HRV, SCR) [40]. EEG needs accurate measurement and analyzing time which makes it hard to be used in daily life. Also, ordinary people lack professional information to use EEG [47]. Therefore, I combined HRV data which is easy to measure and analyze to compensate the disadvantages and increase accuracy. As a result, I found out that it increases predictability if we combined the EEG data and HRV data compared to

using only EEG measurement (fig. 5, 7). This is because HRV data is also related to cognitive performance. Also, measuring physiological signals with combination of EEG and HRV reduces the risk of noise of signals which may affects the predictability of model.

4.2. With the specific area (occipital, O2), Memory can be predictable. Moreover, with the addition of HRV data, predictability increased. As a result, Occipital (O2) predicts memory mostly.

We can predict memory ability with signals from specific area. With the addition of HRV data, it increases predictability. Also, framework which predicts memory ability did not analyzed with each variables. I selected specific variable among all variables to discriminate the most predictable variables. As a result, occipital area was most predictable variable which predicts memory ability (fig. 6). However, I did

not find the brain wave which significantly predicts memory ability fig. 7C, D). According to previous studies, digit span task involves more complicated processing and thus calls for a larger involvement of the central executive resources [45]. There are researches demonstrating activation in occipital area during forward and backward digit span task. The reason there are no memory prediction model based on brainwave is that there are no variable significantly affects prediction [48]. It can be inferred with the statistical data which has similar R-squared and p-value in the results.

Figure 8

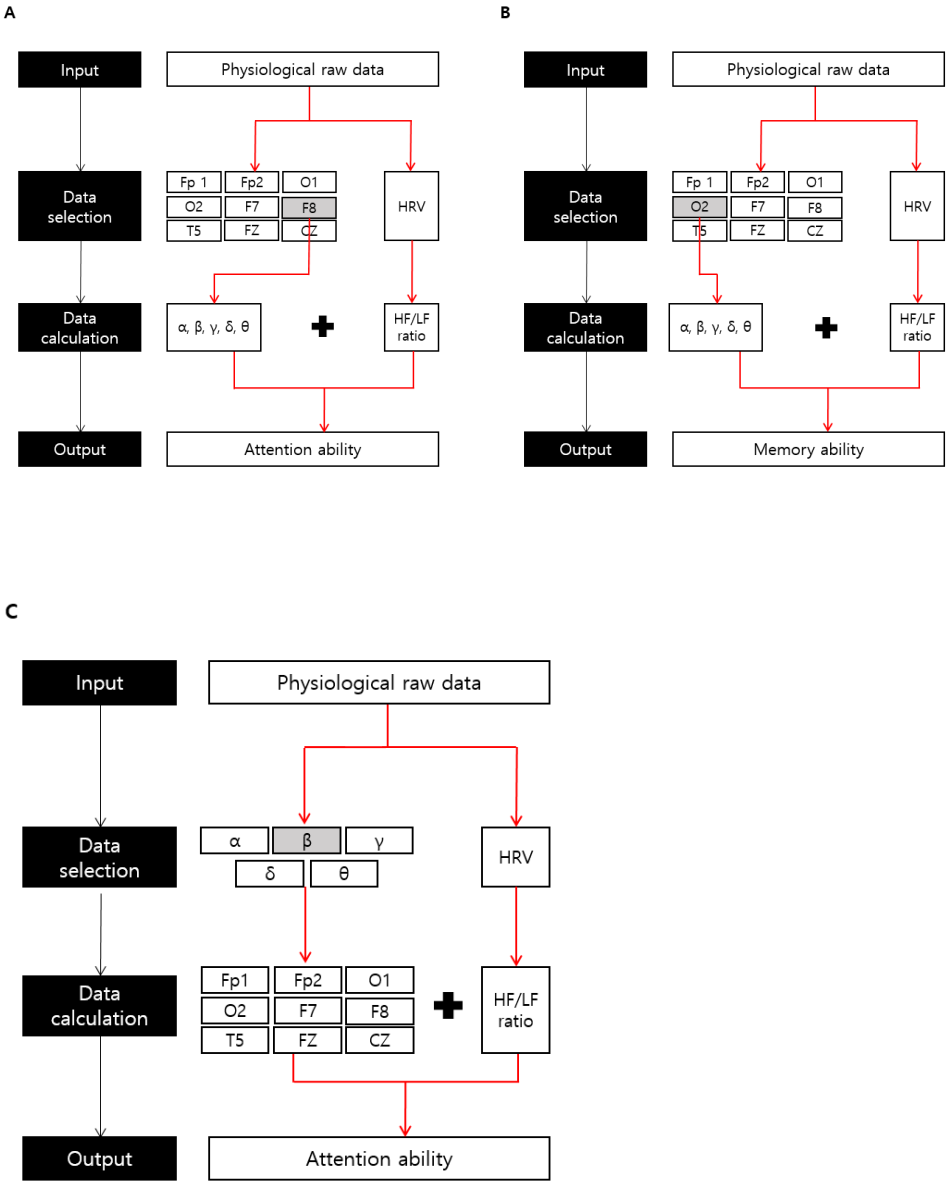

A
Input
Physiological raw data
Data selection
Fp 1
Fp2
O1
O2
F7
F8
T5
FZ
CZ
HRV
Data calculation
α, β, γ, δ, θ
HF/LF ratio
Output
Attention ability
B
Input
Physiological raw data
Data selection
Fp 1
Fp2
O1
O2
F7
F8
T5
FZ
CZ
HRV
Data calculation
α, β, γ, δ, θ
HF/LF ratio
Output
Memory ability
C
Input
Physiological raw data
Data selection
α
β
γ
δ
θ
HRV
Data calculation
Fp1
Fp2
O1
O2
F7
F8
T5
FZ
CZ
HF/LF ratio
Output
Attention ability

Figure 8. Algorithm formula application process based on the results of the research. (A), (B) When the user wants to check the attention and memory ability, it is possible to predict the attention and memory ability by only one (F8 or O2) without using several electrodes. Also when the user input raw data, attention and memory ability was predicted without any process. And HRV data is combined in all processes to increase the prediction accuracy. (C) Attention ability can be predicted by the same process with the brain wave as well as the brain region.

4.3. Physiological data as real-time indicator in daily life.

I tried to demonstrate the accuracy of predicting attention and memory ability by physiological combination [49]. This study aims to develop minimal framework which is clinically achievable by overcoming disadvantages not technical improvement. Framework sets guidelines to select most meaningful information predicting attention and memory ability from the measured physiological raw data [40]. Therefore, this study decreases misuse of physiological measurement so that people can simply use physiological data as real-time indicator without professional knowledge. The further study will be applicated to other stages of ages not only children in concrete operational stage to develop psychological indicator for the wellness life. Systems which helps interaction between human and technologies increase performances and productivities in daily life, workplace and for educational use [50]. For this goal, there are problems which help monitoring mental health state. First, we have to define measuring tool which can steadily work. Second, I have to

increase the number of participants to increase the accuracy of prediction. Also, with the combination of other physiological measurement (ex>skin conductance response, breath rate), ultimately we have to develop the integrated physiological measurement framework for mental health assessment. Lastly, Framework of this study needs compatibility with physiological measurement for selection of user's physiological raw data. Additional UX/UI applications are needed to be easily used in daily life. There are previous studies that physiological data are used as meaningful clinical information for clinical cure. However, there are no combination between technologies for ordinary people compared to technical improvement [51]. Ordinary people needs the system which can trach their maximum mental capacity and manage it. For this, index (mental state gauge) is needed as real-time indicator. It will increase the quality of daily life [52]. This is pilot study which is for people who eager to manage their proper health state to measure and analyze their state. I will broaden my study to larger scope for the wellness life.

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Ⅵ. 국문 초록

원하는 성과를 내는 것은 일을 할 때뿐만 아니라 일상생활에서 중요한 요인이다. 이때 성과는 수행자의 정신적으로 수용한 가능한 능력과 정신적 과부하에 따라 영향을 받는다. 수행자가 수용 가능한 능력을 작업량이 초과할 경우 성과는 감소하게 된다. 작업량이 수용 능력을 초과하는 이 지점을 인지적 과부하가 발생한 레드라인이라고 지칭한다. 이 지점부터는 성과는 빠른 속도로 감소하기 때문에 인지적 레드라인에 관한 선행 연구들이 수행되었다. 즉, 좋은 성과를 위해서는 신체적인 작업량만큼이나 정신적으로 과부하에 걸렸는가도 중요하다. 특히, 피아제의 인지발달이론에 따르면, 구체적 조작기에 있는 아동들은 질과 양을 구분하는 능력이 발달하기 시작하는 시기로 향후 학습에 매우 중요한 시기이다.

하지만 정신적 과부하는 생리학적 측정을 통해 정량화하기 어렵

기 때문에 이를 통해 인지적 레드라인을 증명하기에 복잡하다. 게다가 생리학적 측정의 대표적인 EEG는 두뇌의 신호를 측정해 낼 수 있지만 정확한 측정과정과 전문적인 분석과정이 필요하다. 또 다른 생리학적 측정 방법인 HRV의 경우 상대적으로 측정방법은 간단하나 두뇌를 직접적으로 측정하지 않는다는 단점이 있다. 또한 앞서 언급한 것처럼 많은 연구자들이 생리학적 측정 방법을 이용하여 실생활 지표로 사용하려고 하고 있으나 이들간 통합이 되지 않았다.

그러므로 본 연구에서는 향후 학습 능력에 중요한 시기에 있는 아동들의 정신적 수용능력(집중력, 기억력)을 EEG로 예측하여 정신적 과부하를 예방할 수 있도록 시도하였다. 또한 이에 HRV를 조합하여 각 생리학적 측정 방법의 단점을 보완하여 더 정확한 정신적 수용능력(집중력, 기억력) 예측 알고리즘을 만들고자 하였다. 6-13세의 초등학생들을 대상으로 피아제 이론에 근거하여 집중력

은 Stroop task, 기억력은 digit span task를 통해 측정하였다.

결론적으로, 집중력과 기억력을 가장 잘 예측할 수 있는 뇌부위는 각각 우측두엽과 후두엽으로 확인하였다. 그리고 뇌 파장 별로는 베타파가 가장 집중력을 가장 잘 예측하는 것으로 확인하였으나, 기억력 관련해서는 발견하지 못하였다. 하지만, 위 결과에 HRV를 추가하여 집중력과 기억력을 더 잘 예측할 수 있는 알고리즘 모델을 만들어 내었다. 그리고 본 연구는 이를 공식화하여 일상생활에서 집중력과 기억력을 생리학적 데이터를 이용해 더 높은 정확도로 쉽게 확인 할 수 있도록 하였다.

본 연구에서는 기존에 통합되지 않은 생리학적 데이터를 통합함으로써, 각 생리학적 데이터들의 단점을 보완하고 더 높은 정확도의 모델을 만들어 실생활에서 사용할 수 있는 정신적 지표의 방향성을 제시하였다.

향후 더 많은 피험자들의 참가를 바탕으로 빅데이터화 하여 모델

의 정확도를 높일 필요성이 있다. 또한 본 연구결과의 활용을 위해 다양한 웨어러블 기기들과 연동은 물론 사용자의 데이터를 수집하고 분석할 수 있는 어플리케이션들의 개발이 필요하다.

주요어: 생리학적 데이터, EEG, HRV, 조합, 예측, 집중력, 기억력, 알고리즘 모델

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